

# SDE-based Generative Models

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SP in CVL

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- NCSN
- DDPM
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# Noise Conditional Score Network (NCSN)\*

**Motivation:** Learning the score function  $s_\theta(x) \sim \nabla_x \log p(x)$  instead

**Training Objective:** Score Matching for Score Estimation

$$\frac{1}{2} \mathbb{E}_{p_{data}} [ \| s_\theta(x) - \nabla_x \log p_{data}(x) \|_2^2 ] \longrightarrow \mathbb{E}_{p_{data}} \left[ \underbrace{\text{tr}(\nabla_x s_\theta(x))}_{\text{expensive}} + \frac{1}{2} \| s_\theta(x) \|_2^2 \right]$$

**Sampling with Langevin Dynamics**

$$x_t = x_{t-1} + \frac{\epsilon}{2} \underbrace{\nabla_x \log p(x_{t-1})}_{\text{score}} + \sqrt{\epsilon} z_t, \quad \text{where } z_t \sim \mathcal{N}(0, \mathbf{I})$$

# Noise Conditional Score Network (NCSN)

## Cheaper Score Matching

### 1. Denoising Score Matching (DSM)

pre-specified noise distribution, i.e. Gaussian

$$\text{Matching perturbed data distribution } q_\sigma(\tilde{x}) = \int \underline{q_\sigma(\tilde{x}|x)p_{data}(x)} dx$$

$$\frac{1}{2} \mathbb{E}_{q_\sigma(\tilde{x}|x)p_{data}(x)} [ \| s_\theta(\tilde{x}) - \nabla_{\tilde{x}} \log q_\sigma(\tilde{x}|x) \|_2^2 ]$$

### 2. Sliced Score Matching: random projections to approximate $\text{tr}(\nabla_x s_\theta(x))$

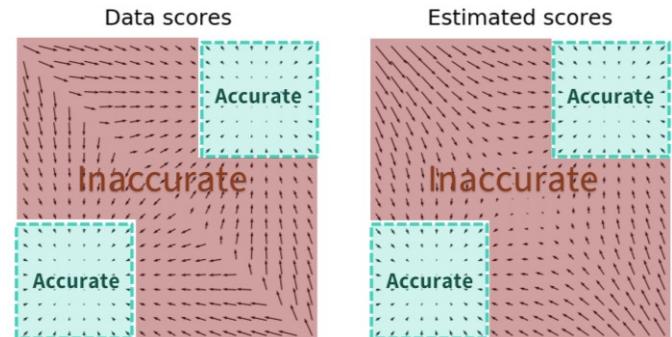
$$\mathbb{E}_{p_v} \mathbb{E}_{p_{data}} \left[ v^T s_\theta(x)v - \frac{1}{2} \| s_\theta(x) \|_2^2 \right]$$

# Noise Conditional Score Network (NCSN)

## Low Density Regions Pitfalls

1. Inaccurate score estimation in low data density regions

For regions with  $p_{data} \approx 0$ , we do not have sufficient data samples for accurate estimation.

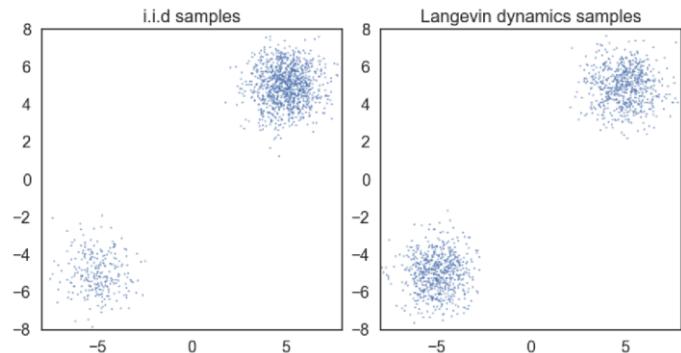


2. Slow mixing of Langevin dynamic

$$p_{data}(x) = \pi p_1(x) + (1 - \pi)p_2(x)$$

$$\nabla_x \log p_{data}(x) = \nabla_x \log p_1(x)$$

$$\nabla_x \log p_{data}(x) = \nabla_x \log p_2(x)$$



# Noise Conditional Score Network (NCSN)

**Training Objective:** Score Matching a Sequence of Noise-levels

**Large noise:** perturbate the data sufficiently to better estimate the low density regions

**Small noise:** be able to converge to the true data distribution

Denoising score matching objective for given  $\sigma$

$$q_\sigma(\tilde{x}|x) = \mathcal{N}(\tilde{x} | x, \sigma^2 \mathbf{I}) \longrightarrow \nabla_x \log q_\sigma(\tilde{x}|x) = -(\tilde{x} - x)/\sigma^2$$

$$\ell(\theta; \sigma) \triangleq \frac{1}{2} \mathbb{E}_{p_{data}(x)} \mathbb{E}_{\tilde{x} \sim \mathcal{N}(x, \sigma^2 \mathbf{I})} \| s_\theta(\tilde{x}, \sigma) + \frac{\tilde{x} - x}{\sigma^2} \|_2^2$$

Final objective

$$\mathcal{L}(\theta; \{\sigma_i\}_{i=1}^L) \triangleq \frac{1}{L} \sum_{i=1}^L \underline{\lambda(\sigma_i)} \ell(\theta; \sigma_i)$$

coefficient function

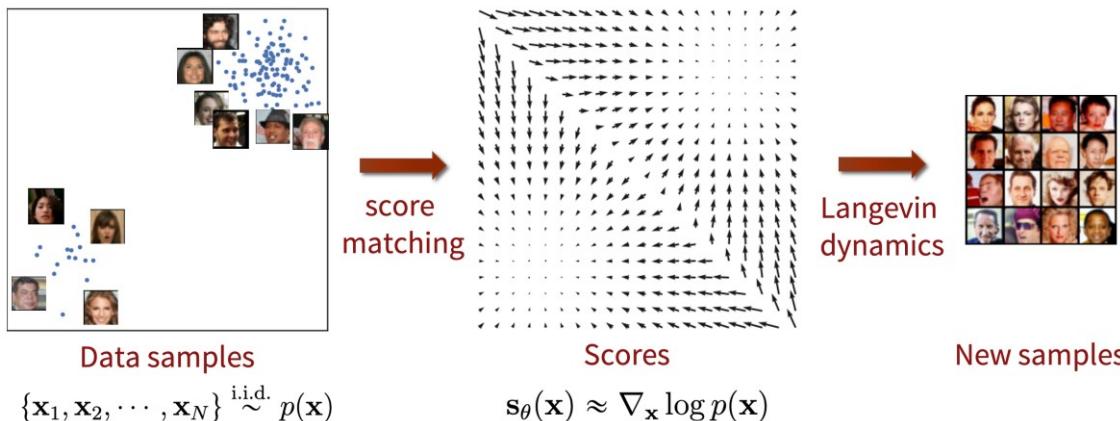
# Noise Conditional Score Network (NCSN)

**NCSN Inference:** via Annealed Langevin Dynamics

A sequence of positive noise scales  $\sigma_{min} = \sigma_1 < \sigma_2 < \dots < \sigma_L = \sigma_{max}$

$$p_{\sigma_{min}}(x) \approx p_{data}(x)$$

$$p_{\sigma_{max}}(x) \approx \mathcal{N}(x; 0, \sigma_{max}^2 \mathbf{I})$$



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**Algorithm 1** Annealed Langevin dynamics.

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**Require:**  $\{\sigma_i\}_{i=1}^L, \epsilon, T$ .

- 1: Initialize  $\tilde{\mathbf{x}}_0$
- 2: **for**  $i \leftarrow L$  to 1 **do**
- 3:      $\alpha_i \leftarrow \epsilon \cdot \sigma_i^2 / \sigma_L^2$       $\triangleright \alpha_i$  is the step size.
- 4:     **for**  $t \leftarrow 1$  to  $T$  **do**
- 5:         Draw  $\mathbf{z}_t \sim \mathcal{N}(0, I)$
- 6:          $\tilde{\mathbf{x}}_t \leftarrow \tilde{\mathbf{x}}_{t-1} + \frac{\alpha_i}{2} \mathbf{s}_{\theta}(\tilde{\mathbf{x}}_{t-1}, \sigma_i) + \sqrt{\alpha_i} \mathbf{z}_t$
- 7:     **end for**
- 8:      $\tilde{\mathbf{x}}_0 \leftarrow \tilde{\mathbf{x}}_T$
- 9: **end for**
- return**  $\tilde{\mathbf{x}}_T$

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# Deep Unsupervised Learning using Nonequilibrium Thermodynamics\*

First Attempt from *Deep Unsupervised Learning using Nonequilibrium Thermodynamics*

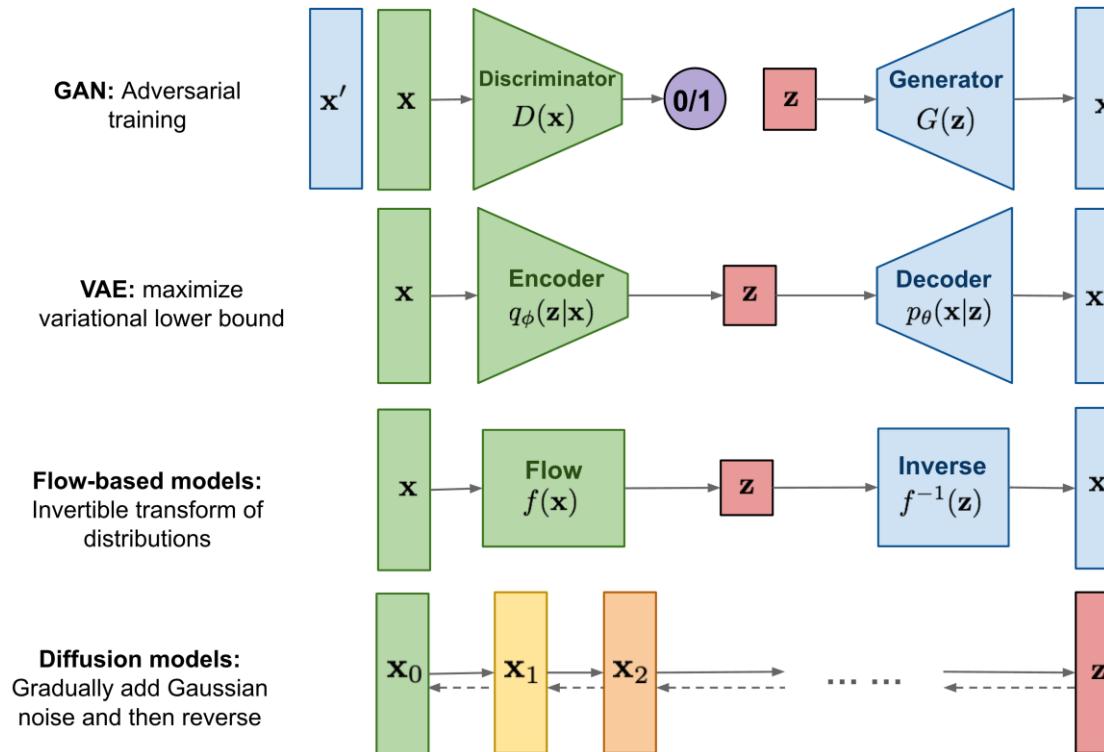
Main Ideas:

- inspired by non-equilibrium statistical physics
- systematically and slowly destroy structure in a data distribution (iterative forward diffusion)
- then **learn a reverse diffusion process** that restores structure in data(restore data distribution)

Math come soon in DDPM

**Jascha Sohl-Dickstein** is also author of *RealNVP* and *Score-based generative model through SDE*, now is working on ML theory and NLP

# DDPM: Denoising Diffusion Probabilistic Models\*



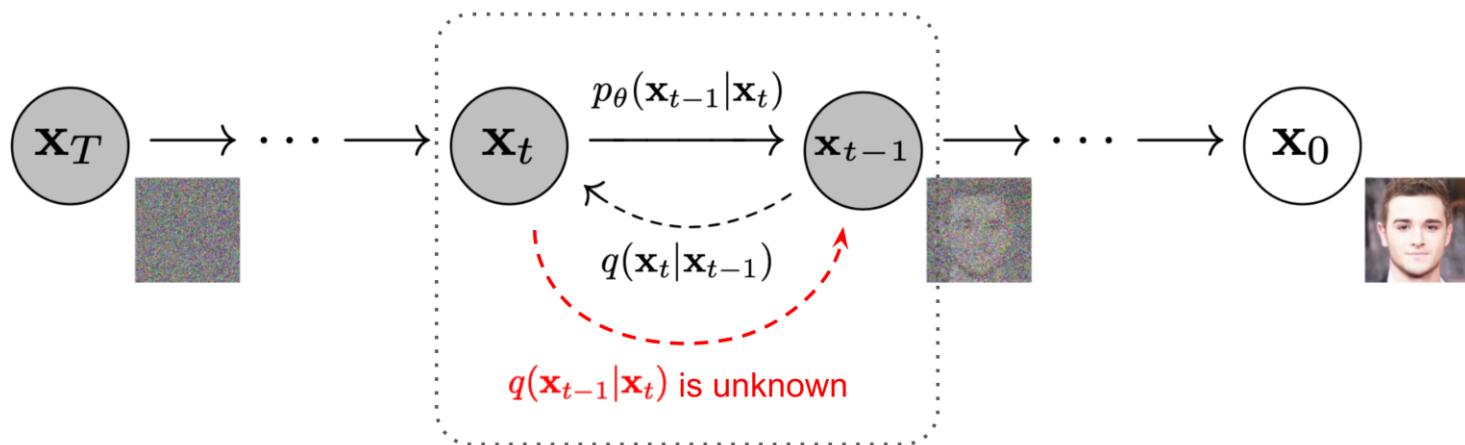
# DDPM: Denoising Diffusion Probabilistic Models

True data dist. :  $x_0 \sim q(x_0)$

Forward process:  $q(x_{1:T}|x_0) := \prod_{t=1}^T q(x_t|x_{t-1})$  Markov Assumption

Reverse process:  $p_\theta(x_{0:T}) := p(x_T) \prod_{t=1}^T p_\theta(x_{t-1}|x_t)$

Use variational lower bound



# DDPM: Denoising Diffusion Probabilistic Models

## Forward Diffusion Process

$$q(x_{1:T}|x_0) := \prod_{t=1}^T q(x_t|x_{t-1})$$

Each Step

$$q(x_t|x_{t-1}) = \mathcal{N}(x_t; \underbrace{\sqrt{1 - \beta_t}x_{t-1}}_{\text{norm invariant}}, \beta_t \mathbf{I}) \quad \text{or} \quad x_t = \sqrt{1 - \beta_t}x_{t-1} + \sqrt{\beta_t}z_{t-1}$$

variance schedule  $\beta_t$  controls the diffusion processing

For arbitrary  $t$

$$q(x_t|x_0) = \mathcal{N}(x_t; \sqrt{\bar{\alpha}_t}x_0, (1 - \bar{\alpha}_t)\mathbf{I}) \quad \alpha_t = 1 - \beta_t \text{ and } \bar{\alpha}_t = \prod_{i=1}^T \alpha_i$$

# DDPM: Denoising Diffusion Probabilistic Models

**Reverse Diffusion Process**

if  $\beta_t$  is small enough,  $q(x_{t-1}|x_t)$  will also be Gaussian

$$p_\theta(x_{0:T}) = p(x_T) \prod_{t=1}^T p_\theta(x_{t-1}|x_t) \quad p_\theta(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \boldsymbol{\mu}_\theta(x_t, t), \boldsymbol{\Sigma}_\theta(x_t, t))$$

Reverse when condition on  $x_0$

$$\begin{aligned} & q(x_{t-1}|x_t, x_0) \\ &= q(x_t|x_{t-1}, x_0) \frac{q(x_{t-1}|x_0)}{q(x_t|x_0)} \\ &\propto \exp \left( -\frac{1}{2} \left( \frac{(x_t - \sqrt{\alpha_t} x_{t-1})^2}{\beta_t} + \frac{(x_{t-1} - \sqrt{\bar{\alpha}_{t-1}} x_0)^2}{1-\bar{\alpha}_{t-1}} - \frac{(x_t - \sqrt{\bar{\alpha}_t} x_0)^2}{1-\bar{\alpha}_t} \right) \right) \\ &= \exp \left( -\frac{1}{2} \left( \left( \frac{\alpha_t}{\beta_t} + \frac{1}{1-\bar{\alpha}_{t-1}} \right) x_{t-1}^2 - \left( \frac{2\sqrt{\alpha_t}}{\beta_t} x_t + \frac{2\sqrt{\bar{\alpha}_{t-1}}}{1-\bar{\alpha}_{t-1}} x_0 \right) x_{t-1} + C(x_t, x_0) \right) \right) \\ &\longrightarrow q(x_{t-1}|x_t, x_0) = \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0), \tilde{\boldsymbol{\beta}}_t \mathbf{I}) \end{aligned}$$

$$\frac{\sqrt{\alpha_t}(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t} x_t + \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1-\bar{\alpha}_t} x_0 = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}} \mathbf{z}_t \right)$$

$$\frac{1-\bar{\alpha}_{t-1}}{1-\bar{\alpha}_t} \cdot \beta_t$$

# DDPM: Denoising Diffusion Probabilistic Models

## Negative Log Likelihood to Variational Lower Bound

$$\begin{aligned} -\log p_\theta(\mathbf{x}_0) &\leq -\log p_\theta(\mathbf{x}_0) + D_{\text{KL}}(q(\mathbf{x}_{1:T}|\mathbf{x}_0)\|p_\theta(\mathbf{x}_{1:T}|\mathbf{x}_0)) \\ &= -\log p_\theta(\mathbf{x}_0) + \mathbb{E}_{\mathbf{x}_{1:T} \sim q(\mathbf{x}_{1:T}|\mathbf{x}_0)} \left[ \log \frac{q(\mathbf{x}_{1:T}|\mathbf{x}_0)}{p_\theta(\mathbf{x}_{0:T})/p_\theta(\mathbf{x}_0)} \right] \\ &= -\log p_\theta(\mathbf{x}_0) + \mathbb{E}_q \left[ \log \frac{q(\mathbf{x}_{1:T}|\mathbf{x}_0)}{p_\theta(\mathbf{x}_{0:T})} + \log p_\theta(\mathbf{x}_0) \right] \\ &= \mathbb{E}_q \left[ \log \frac{q(\mathbf{x}_{1:T}|\mathbf{x}_0)}{p_\theta(\mathbf{x}_{0:T})} \right] \\ \text{Let } L_{\text{VLB}} &= \mathbb{E}_{q(\mathbf{x}_{0:T})} \left[ \log \frac{q(\mathbf{x}_{1:T}|\mathbf{x}_0)}{p_\theta(\mathbf{x}_{0:T})} \right] \geq -\mathbb{E}_{q(\mathbf{x}_0)} \log p_\theta(\mathbf{x}_0) \end{aligned}$$

# DDPM: Denoising Diffusion Probabilistic Models

## Parameterization for Training Loss

$$\begin{aligned}
 L_{\text{VLB}} &= \mathbb{E}_{q(\mathbf{x}_{0:T})} \left[ \log \frac{q(\mathbf{x}_{1:T} | \mathbf{x}_0)}{p_\theta(\mathbf{x}_{0:T})} \right] = \mathbb{E}_q \left[ \log \frac{\prod_{t=1}^T q(\mathbf{x}_t | \mathbf{x}_{t-1})}{p_\theta(\mathbf{x}_T) \prod_{t=1}^T p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t)} \right] \\
 &= \mathbb{E}_q \left[ \log \frac{q(\mathbf{x}_T | \mathbf{x}_0)}{p_\theta(\mathbf{x}_T)} + \sum_{t=2}^T \log \frac{q(\mathbf{x}_{t-1} | \mathbf{x}_t, \mathbf{x}_0)}{p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t)} - \log p_\theta(\mathbf{x}_0 | \mathbf{x}_1) \right] \xrightarrow{\text{Known}} \\
 &= \mathbb{E}_q \underbrace{[D_{\text{KL}}(q(\mathbf{x}_T | \mathbf{x}_0) \| p_\theta(\mathbf{x}_T))]}_{L_T} + \sum_{t=2}^T \underbrace{D_{\text{KL}}(q(\mathbf{x}_{t-1} | \mathbf{x}_t, \mathbf{x}_0) \| p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t))}_{L_t} \underbrace{- \log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)}_{L_0}
 \end{aligned}$$

$$p_\theta(x_{t-1} | x_t) = \mathcal{N}(x_{t-1}; \boldsymbol{\mu}_\theta(x_t, t), \boldsymbol{\Sigma}_\theta(x_t, t)) \quad \begin{cases} \boldsymbol{\mu}_\theta(x_t, t) = \frac{1}{\sqrt{\alpha_t}}(x_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}z_\theta(x_t, t)) \\ \boldsymbol{\Sigma}_\theta(x_t, t) = \sigma_t^2 \mathbf{I} \end{cases}$$

## Model The Noise(Residual)

$$L_t^{\text{simple}} = \mathbb{E}_{x_0, z_t} \left[ \|z_t - z_\theta(\sqrt{\bar{\alpha}_t}x_0 + \sqrt{1-\bar{\alpha}_t}z_t, t)\|^2 \right]$$

# DDPM: Denoising Diffusion Probabilistic Models

Nonetheless, it is just **another parameterization** of  $p_\theta(x_{t-1}|x_t)$

$$p_\theta(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \boldsymbol{\mu}_\theta(x_t, t), \boldsymbol{\Sigma}_\theta(x_t, t))$$

$$\begin{cases} \boldsymbol{\mu}_\theta(x_t, t) = \frac{1}{\sqrt{\alpha_t}}(x_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}z_\theta(x_t, t)) \\ \boldsymbol{\Sigma}_\theta(x_t, t) = \sigma_t^2 \mathbf{I} \end{cases}$$

two options †  $\sigma^2 = \begin{cases} \beta_t \\ \frac{1 - \hat{\alpha}_{t-1}}{1 - \hat{\alpha}_t} \beta_t \end{cases}$

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## Algorithm 1 Training

```
1: repeat
2:    $\mathbf{x}_0 \sim q(\mathbf{x}_0)$ 
3:    $t \sim \text{Uniform}(\{1, \dots, T\})$ 
4:    $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
5:   Take gradient descent step on
       $\nabla_\theta \|\epsilon - \mathbf{z}_\theta(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, t)\|^2$ 
6: until converged
```

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## Algorithm 2 Sampling

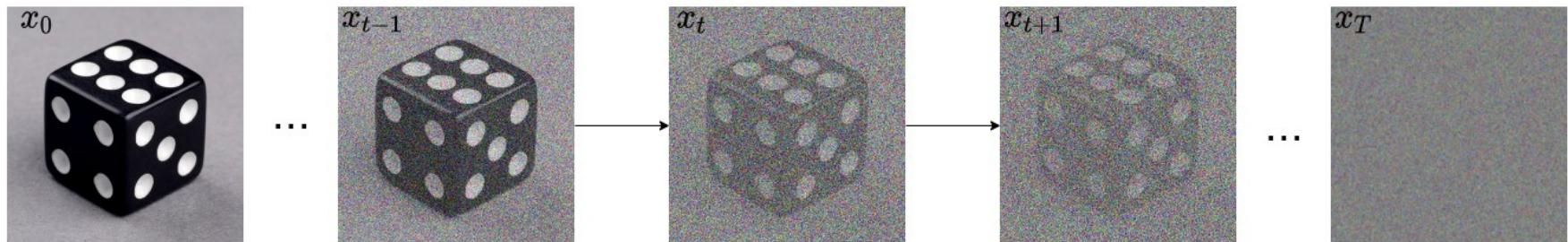
```
1:  $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
2: for  $t = T, \dots, 1$  do
3:    $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$ 
4:    $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \mathbf{z}_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$ 
5: end for
6: return  $\mathbf{x}_0$ 
```

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† Covariance has analytical optimal form ([Estimating the Optimal Covariance with Imperfect Mean in Diffusion Probabilistic Models](#))

# DDPM: Denoising Diffusion Probabilistic Models

$$x_0 \sim q(x_0) \quad \xrightarrow{\text{---}} \quad q(x_t | x_{t-1}) = \mathcal{N}(x_t; \sqrt{1 - \beta_t} x_{t-1}, \beta_t I) \quad \xrightarrow{\text{---}} \quad q(x_{1:T} | x_0) = \prod_{t=1}^T q(x_t | x_{t-1})$$



$$p_\theta(x_0) = \int p(x_T) \prod_{i=1}^T p_\theta(x_{t-1} | x_t) dx_{1:T} \quad \xleftarrow{\text{---}} \quad p_\theta(x_{t-1} | x_t) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t)) \quad \xleftarrow{\text{---}} \quad x_T \sim \mathcal{N}(0, I)$$

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# DDIM: Denoising Diffusion Implicit Models\*

## Variational Inference for *Non-Markovian* Forward Processes

$$-\log p_\theta(\mathbf{x}_0) \leq -\log p_\theta(\mathbf{x}_0) + D_{\text{KL}}(q(\mathbf{x}_{1:T}|\mathbf{x}_0) \| p_\theta(\mathbf{x}_{1:T}|\mathbf{x}_0))$$

Model this directly

$$q_\sigma(x_{1:T}|x_0) = q_\sigma(x_T|x_0) \prod_{t=2}^T q_\sigma(x_{t-1}|x_t, x_0)$$

**Reverse Process:** deterministic given  $x_t, x_0$

$$\begin{aligned} x_{t-1} &= \sqrt{\alpha_{t-1}} x_0 + \sqrt{1 - \alpha_{t-1}} \cdot \epsilon_{t-1} = \sqrt{\alpha_{t-1}} x_0 + \sqrt{1 - \alpha_{t-1} - \sigma_t^2} \cdot \epsilon_t + \sigma_t \epsilon \\ q_\sigma(x_{t-1}|x_t, x_0) &= \mathcal{N}\left(\sqrt{\alpha_{t-1}} x_0 + \sqrt{1 - \alpha_{t-1} - \sigma_t^2} \cdot \frac{x_t - \sqrt{\alpha_t} x_0}{\sqrt{1 - \alpha_t}}, \sigma_t^2 \mathbf{I}\right) \end{aligned}$$

**Forward:** still Gaussian (non-Markovian)

$$q_\sigma(x_t|x_{t-1}, x_0) = \frac{q_\sigma(x_{t-1}|x_t, x_0)q_\sigma(x_t|x_0)}{q_\sigma(x_{t-1}|x_0)}$$

[2010.02502] Denoising Diffusion Implicit Models (arxiv.org)

$\alpha_t$  in DDIM is  $\bar{\alpha}_t$  in DDPM.

# DDIM: Denoising Diffusion Implicit Models

Given: noisy observation  $x_t$

Prediction of the corresponding  $\hat{x}_0(x_t) = f_\theta^{(t)}(x_t) = (x_t - \sqrt{1 - \alpha_t} \epsilon_\theta^{(t)}(x_t)) / \sqrt{\alpha_t}$

Model difference between  $x_0$  and  $x_t$

$$p_\theta^{(t)}(x_{t-1}|x_t) = \begin{cases} \mathcal{N}(f_\theta^{(1)}(x_1), \sigma_1^2 I) & \text{if } t = 1 \\ q_\sigma(x_{t-1}|x_t, f_\theta^{(t)}(x_t)) & \text{otherwise} \end{cases}$$

**Variational Inference Objective** (equivalent to objective in DDPM for certain weights)

$$\begin{aligned} J_\sigma(\epsilon_\theta) &:= \mathbb{E}_{\mathbf{x}_{0:T} \sim q_\sigma(\mathbf{x}_{0:T})} [\log q_\sigma(\mathbf{x}_{1:T}|\mathbf{x}_0) - \log p_\theta(\mathbf{x}_{0:T})] \\ &= \mathbb{E}_{\mathbf{x}_{0:T} \sim q_\sigma(\mathbf{x}_{0:T})} \left[ \log q_\sigma(\mathbf{x}_T|\mathbf{x}_0) + \sum_{t=2}^T \log q_\sigma(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) - \sum_{t=1}^T \log p_\theta^{(t)}(\mathbf{x}_{t-1}|\mathbf{x}_t) - \log p_\theta(\mathbf{x}_T) \right] \end{aligned}$$

**Surrogate Objective**  $L_t^{\text{simple}} = \mathbb{E}_{x_0, z_t} \left[ \|z_t - z_\theta(\sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} z_t, t)\|^2 \right]$

# DDIM: Denoising Diffusion Implicit Models

**Sampling** from Generalized Generative Processes  $p_\theta^{(t)}(x_{t-1}|x_t)$

$$x_{t-1} = \underbrace{\sqrt{\alpha_{t-1}} \left( \frac{x_t - \sqrt{1 - \alpha_t} \epsilon_\theta^{(t)}(x_t)}{\sqrt{\alpha_t}} \right)}_{\text{predicted } x_0} + \underbrace{\sqrt{1 - \alpha_{t-1} - \sigma_t^2} \cdot \epsilon_\theta^{(t)}(x_t)}_{\text{direction pointing to } x_t} + \underbrace{\sigma_t \epsilon_t}_{\text{random noise}}$$

$$\sigma_t := \eta \sqrt{(1 - \alpha_{t-1}) / (1 - \alpha_t)} \sqrt{1 - \alpha_t / \alpha_{t-1}}$$

- **DDPM:**  $\eta = 1$  (forward process becomes Markovian (different noise schedule from vanilla DDPM))
- **DDIM:**  $\eta = 0$  (forward process becomes deterministic)

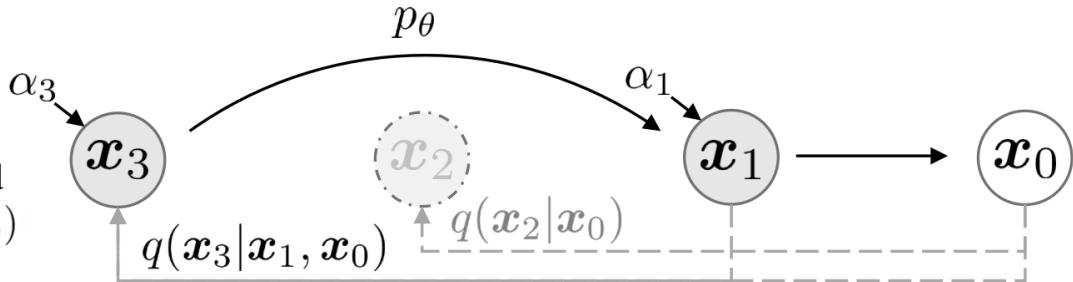
Table 1: CIFAR10 and CelebA image generation measured in FID.  $\eta = 1.0$  and  $\hat{\sigma}$  are cases of **DDPM** (although Ho et al. (2020) only considered  $T = 1000$  steps, and  $S < T$  can be seen as simulating DDPMs trained with  $S$  steps), and  $\eta = 0.0$  indicates **DDIM**.

$S$	CIFAR10 ( $32 \times 32$ )					CelebA ( $64 \times 64$ )				
	10	20	50	100	1000	10	20	50	100	1000
0.0	<b>13.36</b>	<b>6.84</b>	<b>4.67</b>	<b>4.16</b>	4.04	<b>17.33</b>	<b>13.73</b>	<b>9.17</b>	<b>6.53</b>	3.51
0.2	14.04	7.11	4.77	4.25	4.09	17.66	14.11	9.51	6.79	3.64
0.5	16.66	8.35	5.25	4.46	4.29	19.86	16.06	11.01	8.09	4.28
1.0	41.07	18.36	8.01	5.78	4.73	33.12	26.03	18.48	13.93	5.98
$\hat{\sigma}$	367.43	133.37	32.72	9.99	<b>3.17</b>	299.71	183.83	71.71	45.20	<b>3.26</b>

# DDIM: Denoising Diffusion Implicit Models

## Accelerated Generation Processes

Denoising surrogate objective does not depend on the specific forward procedure  $q_\sigma(x_{t-1}|x_0)$



Consider the forward process as defined on a subset  $\tau = [\tau_1, \tau_2, \dots, \tau_{\dim(\tau)}] \subset [1, 2, \dots, T]$

$$q_{\sigma, \tau}(x_{\tau_{i-1}}|x_{\tau_t}, x_0) = \mathcal{N}\left(x_{\tau_{i-1}}; \sqrt{\bar{\alpha}_{t-1}}x_0 + \sqrt{1 - \bar{\alpha}_{t-1} - \sigma_t^2} \frac{x_{\tau_i} - \sqrt{\bar{\alpha}_t}x_0}{\sqrt{1 - \bar{\alpha}_t}}, \sigma_t^2 \mathbf{I}\right)$$

The generative process now samples latent variables according to  $\text{reversed}(\tau)$ , which we term (sampling) *trajectory*

→ Train a model with arbitrary number forward steps but only sample from some of them in the generative process

# DDIM: Denoising Diffusion Implicit Models

## Relevance to Neural ODEs

$$x_{t-1} = \underbrace{\sqrt{\alpha_{t-1}} \left( \frac{x_t - \sqrt{1-\alpha_t} \epsilon_\theta^{(t)}(x_t)}{\sqrt{\alpha_t}} \right)}_{\text{"predicted } x_0 \text{ "}} + \underbrace{\sqrt{1-\alpha_{t-1}-\sigma_t^2} \cdot \epsilon_\theta^{(t)}(x_t)}_{\text{"direction pointing to } x_t \text{ "}} + \underbrace{\sigma_t \epsilon_t}_{\text{random noise}}$$

$$\implies \frac{x_{t-\Delta t}}{\sqrt{\alpha_{t-\Delta t}}} - \frac{x_t}{\sqrt{\alpha_t}} = \left( \sqrt{\frac{1-\alpha_{t-\Delta t}}{\alpha_{t-\Delta t}}} - \sqrt{\frac{1-\alpha_t}{\alpha_t}} \right) \epsilon_\theta^{(t)}(x_t)$$

$$\begin{aligned} \sigma &:= \sqrt{\frac{1-\alpha}{\alpha}} & \implies d\bar{x}(t) &= \epsilon_\theta^{(t)} \left( \frac{\bar{x}(t)}{\sqrt{\sigma^2 + 1}} \right) d\sigma(t) & \text{Variance-Exploding SDE soon} \\ \bar{x} &:= \frac{x}{\sqrt{\alpha}} \end{aligned}$$

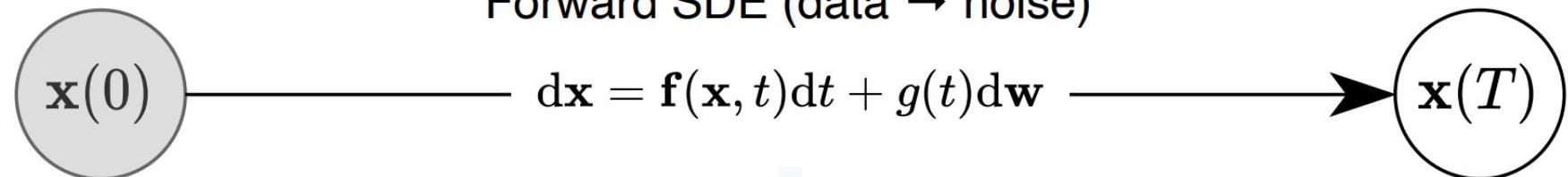
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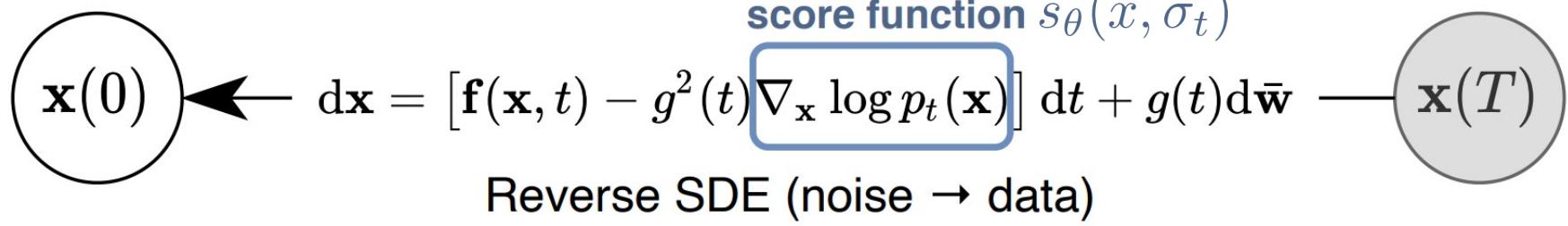
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# SDE-based Generative Models: A Unified Framework\*

Forward SDE (data → noise)



score function  $s_\theta(x, \sigma_t)$



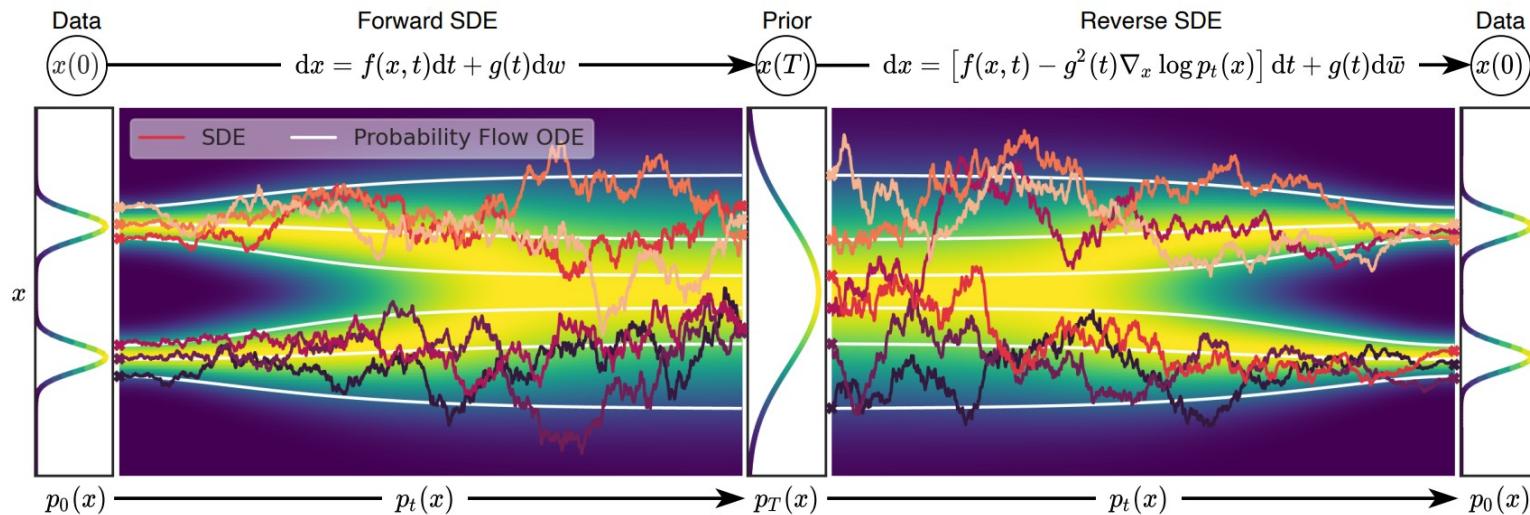
# SDE-based Generative Models: A Unified Framework

Model diffusion process as solution of Itô SDE (continuous time)

$$dx = f(x, t)dt + g(t)dw$$

Generating samples by reversing the SDE

$$dx = [f(x, t) - g(t)^2 \nabla_x \log p_t(x)]dt + g(t)d\bar{w}$$



# SDE-based Generative Models: A Unified Framework

## Training Objective (DSM)

$$\theta^* = \arg \min \mathbb{E}_{t \sim U(0, T)} \left\{ \lambda(t) \mathbb{E}_{x(0)} \mathbb{E}_{x(t)|x(0)} [\| s_\theta(x(t), t) - \nabla_{x(t)} \log p_{0t}(x(t)|x(0)) \|_2^2] \right\}$$

known Gaussian when  $f(x, t)$  if affine

## Discretizations

$$dx = f(x, t)dt + g(t)dw$$

SDE Form	Discrete Markov Chain	SDE Expression
Variance Exploding (VE) SDE (NCSN)	$x_i = x_{i-1} + \sqrt{\sigma_i^2 - \sigma_{i-1}^2} z_{i-1}$	$dx = \sqrt{\frac{d[\sigma^2(t)]}{dt}} dw$
Variance Preserving (VP) SDE (DDPM)	$x_i = \sqrt{1 - \beta_i} x_{i-1} + \sqrt{\beta_i} z_{i-1}$	$dx = \frac{1}{2} \beta(t) x dt + \sqrt{\beta(t)} dw$

# SDE-based Generative Models: A Unified Framework

**Reverse SDE Discretization**  $x_i = x_{i+1} - f_{i+1}(x_{i+1}) + g_{i+1}g_{i+1}^T s_\theta(x_{i+1}, i+1) + g_{i+1}z_{i+1}$

## Predictor-Corrector (PC) Samplers

1. **Predictor:** general-purpose numerical SDE solvers
2. **Corrector:** score-based MCMC (i.e. Langevin MCMC)

DDPM: predictor only  
NCSN: corrector only

---

### Algorithm 2 PC sampling (VE SDE)

```
1:  $\mathbf{x}_N \sim \mathcal{N}(\mathbf{0}, \sigma_{\max}^2 \mathbf{I})$ 
2: for  $i = N - 1$  to 0 do
3:    $\mathbf{x}'_i \leftarrow \mathbf{x}_{i+1} + (\sigma_{i+1}^2 - \sigma_i^2) \mathbf{s}_\theta * (\mathbf{x}_{i+1}, \sigma_{i+1})$ 
4:    $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
5:    $\mathbf{x}_i \leftarrow \mathbf{x}'_i + \sqrt{\sigma_{i+1}^2 - \sigma_i^2} \mathbf{z}$ 
6:   for  $j = 1$  to  $M$  do
7:      $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
8:      $\mathbf{x}_i \leftarrow \mathbf{x}_i + \epsilon_i \mathbf{s}_\theta * (\mathbf{x}_i, \sigma_i) + \sqrt{2\epsilon_i} \mathbf{z}$ 
9:   return  $\mathbf{x}_0$ 
```

---

---

### Algorithm 3 PC sampling (VP SDE)

```
1:  $\mathbf{x}_N \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
2: for  $i = N - 1$  to 0 do
3:    $\mathbf{x}'_i \leftarrow (2 - \sqrt{1 - \beta_{i+1}}) \mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_\theta * (\mathbf{x}_{i+1}, i+1)$ 
4:    $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
5:    $\mathbf{x}_i \leftarrow \mathbf{x}'_i + \sqrt{\beta_{i+1}} \mathbf{z}$ 
6:   for  $j = 1$  to  $M$  do
7:      $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
8:      $\mathbf{x}_i \leftarrow \mathbf{x}_i + \epsilon_i \mathbf{s}_\theta * (\mathbf{x}_i, i) + \sqrt{2\epsilon_i} \mathbf{z}$ 
9:   return  $\mathbf{x}_0$ 
```

---

Predictor

Corrector

# SDE-based Generative Models: A Unified Framework

Relationship between **Bayesian Posterior** and **Reverse SDE**

$$\mathbf{x}_{t+\Delta t} - \mathbf{x}_t = \mathbf{f}_t(\mathbf{x}_t)\Delta t + g_t\sqrt{\Delta t}\boldsymbol{\varepsilon}, \quad \boldsymbol{\varepsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

$$p(\mathbf{x}_{t+\Delta t} | \mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t+\Delta t}; \mathbf{x}_t + \mathbf{f}_t(\mathbf{x}_t)\Delta t, g_t^2 \Delta t \mathbf{I})$$

$$\propto \exp\left(-\frac{\|\mathbf{x}_{t+\Delta t} - \mathbf{x}_t - \mathbf{f}_t(\mathbf{x}_t)\Delta t\|^2}{2g_t^2 \Delta t}\right)$$

$$p(\mathbf{x}_t | \mathbf{x}_{t+\Delta t}) = \frac{p(\mathbf{x}_{t+\Delta t} | \mathbf{x}_t)p(\mathbf{x}_t)}{p(\mathbf{x}_{t+\Delta t})} = p(\mathbf{x}_{t+\Delta t} | \mathbf{x}_t) \exp(\log p(\mathbf{x}_t) - \log p(\mathbf{x}_{t+\Delta t}))$$

$$\propto \exp\left(-\frac{\|\mathbf{x}_{t+\Delta t} - \mathbf{x}_t - \mathbf{f}_t(\mathbf{x}_t)\Delta t\|^2}{2g_t^2 \Delta t} + \log p(\mathbf{x}_t) - \log p(\mathbf{x}_{t+\Delta t})\right)$$

$$\log p(\mathbf{x}_{t+\Delta t}) \approx \log p(\mathbf{x}_t) + (\mathbf{x}_{t+\Delta t} - \mathbf{x}_t) \cdot \nabla_{\mathbf{x}_t} \log p(\mathbf{x}_t) + \Delta t \frac{\partial}{\partial t} \log p(\mathbf{x}_t)$$

$$p(\mathbf{x}_t | \mathbf{x}_{t+\Delta t}) \propto \exp\left(-\frac{\|\mathbf{x}_{t+\Delta t} - \mathbf{x}_t - [\mathbf{f}_t(\mathbf{x}_t) - g_t^2 \nabla_{\mathbf{x}_t} \log p(\mathbf{x}_t)]\Delta t\|^2}{2g_t^2 \Delta t}\right)$$

$$\approx \exp\left(-\frac{\|\mathbf{x}_t - \mathbf{x}_{t+\Delta t} + [\mathbf{f}_{t+\Delta t}(\mathbf{x}_{t+\Delta t}) - g_{t+\Delta t}^2 \nabla_{\mathbf{x}_{t+\Delta t}} \log p(\mathbf{x}_{t+\Delta t})]\Delta t\|^2}{2g_{t+\Delta t}^2 \Delta t}\right)$$

$$d\mathbf{x} = [\mathbf{f}_t(\mathbf{x}) - g_t^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x})] dt + g_t d\mathbf{w}$$

# SDE-based Generative Models: A Unified Framework

**Sampling:** DDPM and SDE point of views (equivalent up to first order)

The ancestral sampling of DDPM matches its reverse diffusion counterpart when  $\beta_i \approx 0$  for all  $i$

Bayesian Posterior

Reverse SDE

$$\begin{aligned}\mathbf{x}_i &= \frac{1}{\sqrt{1 - \beta_{i+1}}} (\mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1)) + \sqrt{\beta_{i+1}} \mathbf{z}_{i+1} \\ &= \left(1 + \frac{1}{2} \beta_{i+1} + o(\beta_{i+1})\right) (\mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1)) + \sqrt{\beta_{i+1}} \mathbf{z}_{i+1} \\ &\approx \left(1 + \frac{1}{2} \beta_{i+1}\right) (\mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1)) + \sqrt{\beta_{i+1}} \mathbf{z}_{i+1} \\ &= \left(1 + \frac{1}{2} \beta_{i+1}\right) \mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1) + \frac{1}{2} \beta_{i+1}^2 \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1) + \sqrt{\beta_{i+1}} \mathbf{z}_{i+1} \\ &\approx \left(1 + \frac{1}{2} \beta_{i+1}\right) \mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1) + \sqrt{\beta_{i+1}} \mathbf{z}_{i+1} \\ &= \left[2 - \left(1 - \frac{1}{2} \beta_{i+1}\right)\right] \mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1) + \sqrt{\beta_{i+1}} \mathbf{z}_{i+1} \\ &\approx \left[2 - \left(1 - \frac{1}{2} \beta_{i+1}\right) + o(\beta_{i+1})\right] \mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1) + \sqrt{\beta_{i+1}} \mathbf{z}_{i+1} \\ &= (2 - \sqrt{1 - \beta_{i+1}}) \mathbf{x}_{i+1} + \beta_{i+1} \mathbf{s}_{\theta*}(\mathbf{x}_{i+1}, i+1) + \sqrt{\beta_{i+1}} \mathbf{z}_{i+1}.\end{aligned}$$

# SDE-based Generative Models: A Unified Framework

**Model:** DDPM and SDE point of views

Score in score-based model is affine transformation of predicted noise in DDPM

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \cdot \boldsymbol{\varepsilon} \quad \text{Equivalent one step forward}$$

$$\begin{aligned} s_\theta(\mathbf{x}_t, t) &\approx \nabla_{\mathbf{x}_t} \log p(\mathbf{x}_t | \mathbf{x}_0) && \text{Denoising score matching} \\ &= -\frac{\mathbf{x}_t - \sqrt{\bar{\alpha}_t} \mathbf{x}_0}{1 - \bar{\alpha}_t} && \text{Gaussian assumption} \\ &= -\frac{\boldsymbol{\varepsilon}}{\sqrt{1 - \bar{\alpha}_t}} && \leftarrow \\ &\approx -\frac{\boldsymbol{\varepsilon}_\theta(\mathbf{x}_t, t)}{\sqrt{1 - \bar{\alpha}_t}} \end{aligned}$$

# SDE-based Generative Models: A Unified Framework

## ODE form

Fokker-Plank function associated with forward diffusion

$$\frac{\partial}{\partial t} p_t(\mathbf{x}) = -\nabla_{\mathbf{x}} \cdot [\mathbf{f}_t(\mathbf{x}) p_t(\mathbf{x})] + \frac{1}{2} g_t^2 \nabla_{\mathbf{x}} \cdot \nabla_{\mathbf{x}} p_t(\mathbf{x})$$

With  $\sigma_t^2 \leq g_t^2$  and  $\begin{aligned} \mathbf{f}_t &\longrightarrow \mathbf{f}_t(\mathbf{x}) - \frac{1}{2}(g_t^2 - \sigma_t^2) \nabla_{\mathbf{x}} \log p_t(\mathbf{x}) \\ g_t &\longrightarrow \sigma_t \end{aligned}$

$$d\mathbf{x} = \mathbf{f}_t(\mathbf{x}) dt + g_t d\mathbf{w} \quad \xleftarrow{\text{equivalent}} \quad d\mathbf{x} = \left( \mathbf{f}_t(\mathbf{x}) - \frac{1}{2}(g_t^2 - \sigma_t^2) \nabla_{\mathbf{x}} \log p_t(\mathbf{x}) \right) dt + \sigma_t d\mathbf{w}$$

Reverse  $d\mathbf{x} = \left( \mathbf{f}_t(\mathbf{x}) - \frac{1}{2}(g_t^2 + \sigma_t^2) \nabla_{\mathbf{x}} \log p_t(\mathbf{x}) \right) dt + \sigma_t d\mathbf{w}$

ODE  $d\mathbf{x} = \left( \mathbf{f}_t(\mathbf{x}) - \frac{1}{2} g_t^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x}) \right) dt$

Comparing with SDEs, ODEs can be solved with larger step sizes as they have no randomness.

# SDE-based Generative Models: A Unified Framework

## Controllable Generation

$$dx = [f(x, t) - g(t)^2 \underline{\nabla_x \log p_t(x|y)}]dt + g(t)d\bar{w}$$

Bayesian time-dependent classifier

$$dx = \{f(x, t) - g(t)^2 [\nabla_x \log p_t(x) + \nabla_x \log p_t(y|x)]\}dt + g(t)d\bar{w}$$

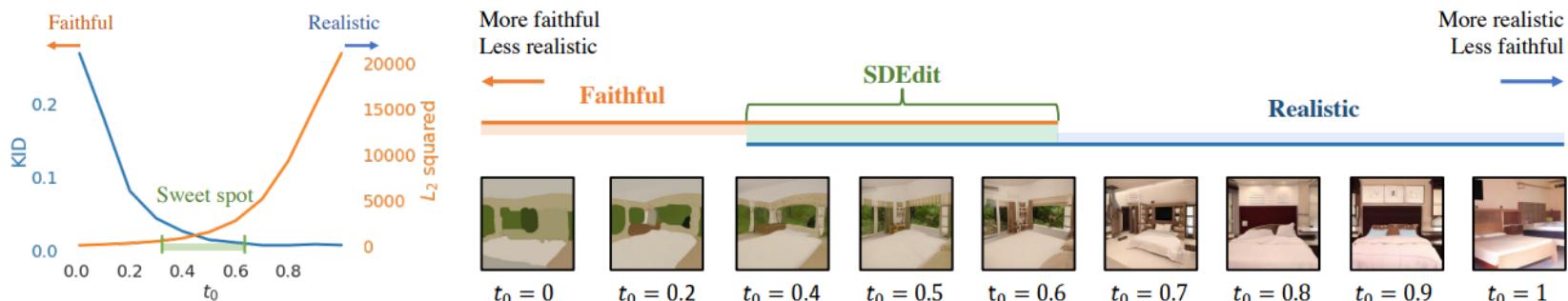
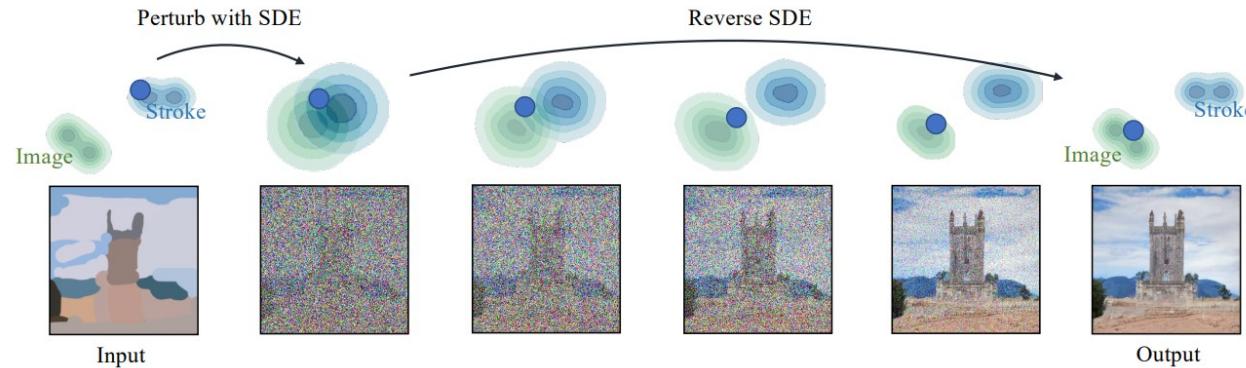


# Content

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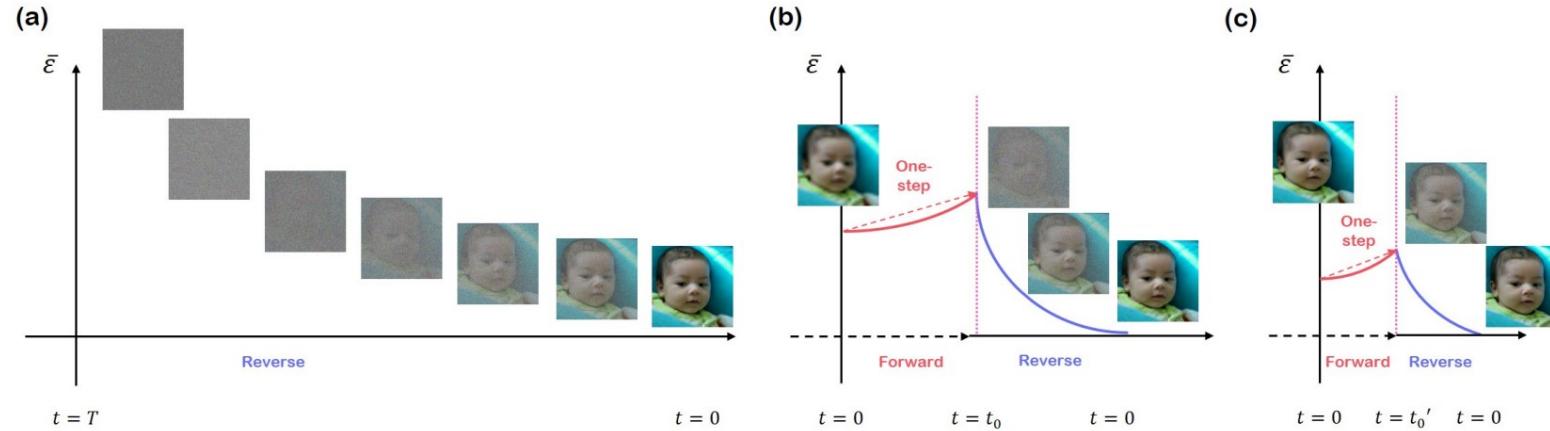
- NCSN
- DDPM
- DDIM
- SDE-based
- Applications

# SDEdit: Guided Image Synthesis and Editing with SDE\*



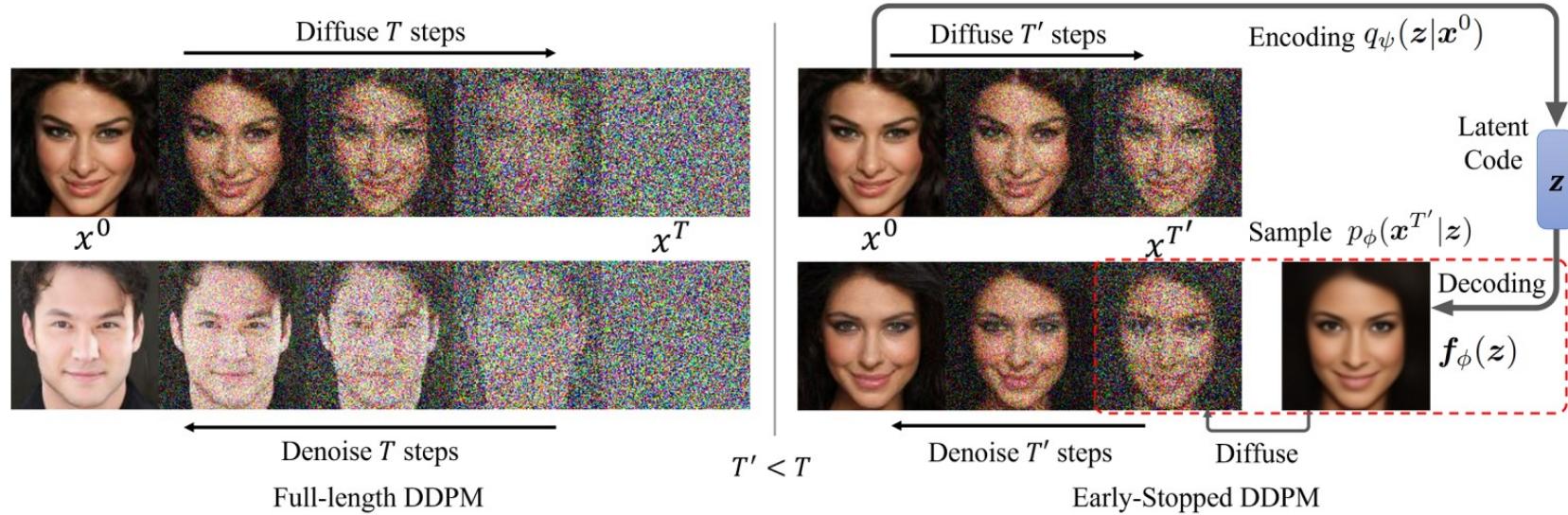
# Come-Closer-Diffuse-Faster: Accelerating Conditional Diffusion Models for Inverse Problems through Stochastic Contraction\*

Same idea but different downstream tasks: super-resolution (SR), inpainting, and MRI reconstruction



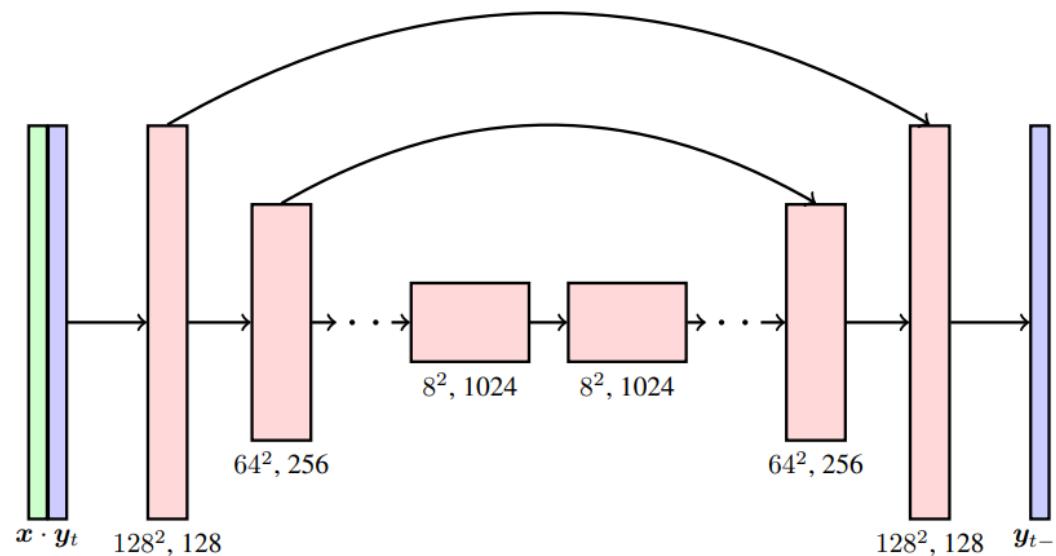
# Accelerating Diffusion Models via Early Stop of the Diffusion Process\*

Get not fully noising image by diffusing output from pre-trained models like GAN and VAE



# Image Super-Resolution via Iterative Refinement\*

The condition is concatenated with  $y_t$  along the channel dimension (cascaded)



Same author also proposed palette for multi-tasks†, same architecture used for cascaded diffusion‡

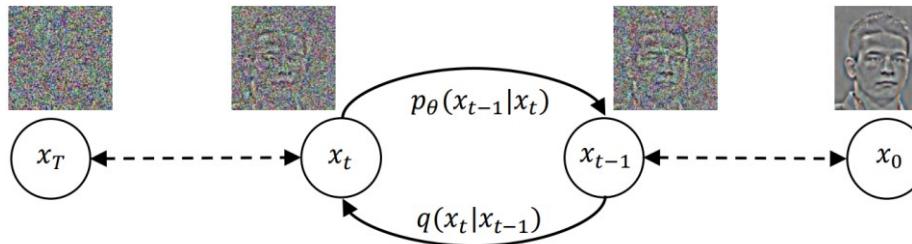
\*[2104.07636] Image Super-Resolution via Iterative Refinement ([arxiv.org/](https://arxiv.org/))

†[2111.05826] Palette: Image-to-Image Diffusion Models ([arxiv.org/](https://arxiv.org/))

‡[2106.15282] Cascaded Diffusion Models for High Fidelity Image Generation ([arxiv.org/](https://arxiv.org/))

# SRDiff: Single Image Super-Resolution with Diffusion Probabilistic Models\*

Learn the residual with condition encoded LR (fused as 2D CNN block outputs )




---

## Algorithm 1 Training

- 1: **Input:** LR image and its corresponding HR image pairs  $P = \{(x_L^k, x_H^k)\}_{k=1}^K$ , total diffusion step  $T$
- 2: **Initialize:** randomly initialized conditional noise predictor  $\epsilon_\theta$  and pretrained LR encoder  $\mathcal{D}$
- 3: **repeat**
- 4:   Sample  $(x_L, x_H) \sim P$
- 5:   Upsample  $x_L$  as  $up(x_L)$ , compute  $x_r = x_H - up(x_L)$
- 6:   Encode LR image  $x_L$  as  $x_e = \mathcal{D}(x_L)$
- 7:   Sample  $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ , and  $t \sim \text{Uniform}(\{1, \dots, T\})$
- 8:   Take gradient step on  

$$\nabla_\theta \|\epsilon - \epsilon_\theta(x_t, x_e, t)\|, x_t = \sqrt{\bar{\alpha}_t} x_r + \sqrt{1 - \bar{\alpha}_t} \epsilon$$
- 9: **until** converged

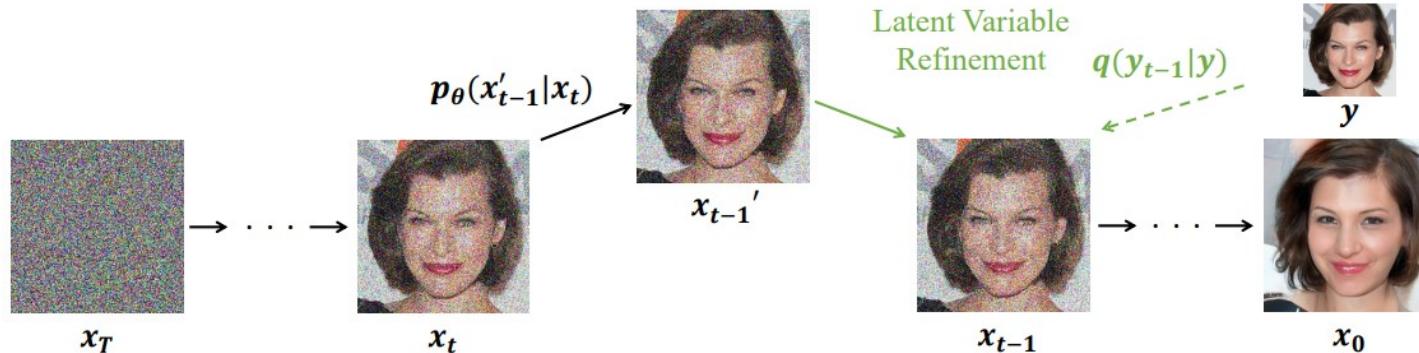
---

## Algorithm 2 Inference

- 1: **Input:** LR image  $x_L$ , total diffusion step  $T$
- 2: **Load:** conditional noise predictor  $\epsilon_\theta$  and LR encoder  $\mathcal{D}$
- 3: Sample  $x_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
- 4: Upsample  $x_L$  to  $up(x_L)$
- 5: Encode LR image  $x_L$  as  $x_e = \mathcal{D}(x_L)$
- 6: **for**  $t = T, T-1, \dots, 1$  **do**
- 7:   Sample  $z \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $z = 0$
- 8:   Compute  $x_{t-1}$  using Eq. (7):  

$$x_{t-1} = \frac{1}{\sqrt{\bar{\alpha}_t}} \left( x_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_\theta(x_t, x_e, t) \right) + \sigma_\theta(x_t, t) z$$
- 9: **end for**
- 10: **return**  $x_0 + up(x_L)$  as SR prediction

# ILVR: Conditioning Method for DDPM\*



---

### Algorithm 1 Iterative Latent Variable Refinement

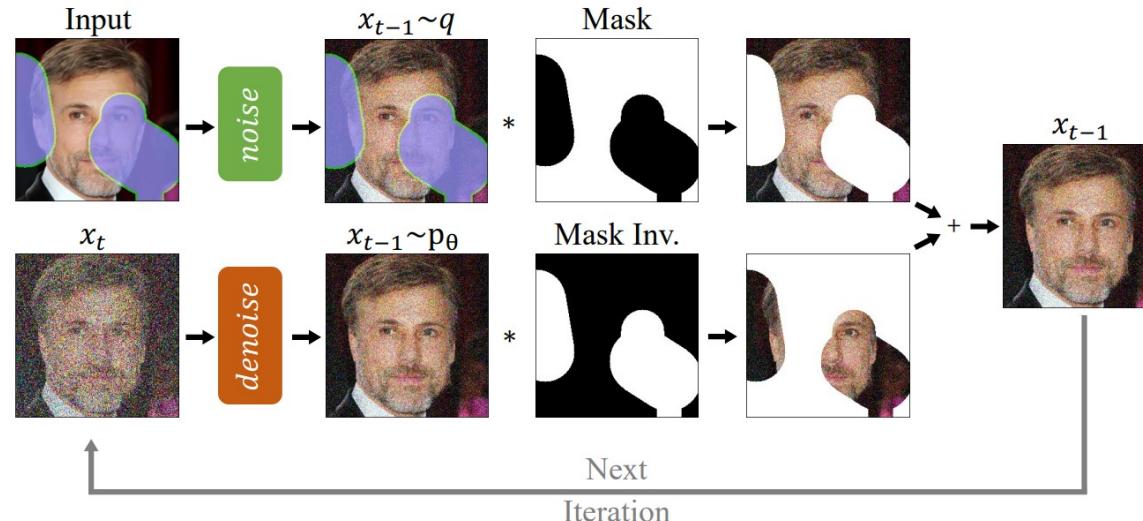
---

```
1: Input: Reference image  $y$ 
2: Output: Generated image  $x$ 
3:  $\phi_N(\cdot)$ : low-pass filter with scale N
4: Sample  $x_T \sim N(\mathbf{0}, \mathbf{I})$ 
5: for  $t = T, \dots, 1$  do
6:    $\mathbf{z} \sim N(\mathbf{0}, \mathbf{I})$ 
7:    $x'_{t-1} \sim p_\theta(x'_{t-1}|x_t)$        $\triangleright$  unconditional proposal
8:    $y_{t-1} \sim q(y_{t-1}|y)$              $\triangleright$  condition encoding
9:    $x_{t-1} \leftarrow \phi_N(y_{t-1}) + x'_{t-1} - \phi_N(x'_{t-1})$ 
10: end for
11: return  $x_0$ 
```

---

# RePaint: Inpainting using Denoising Diffusion Probabilistic Models\*

Same idea but different downstream tasks from ILVR



**Algorithm 1** Inpainting using our RePaint approach.

```
1:  $x_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
2: for  $t = T, \dots, 1$  do
3:   for  $u = 1, \dots, U$  do
4:      $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\epsilon = \mathbf{0}$ 
5:      $x_{t-1}^{\text{known}} = \sqrt{\bar{\alpha}_t} x_0 + (1 - \bar{\alpha}_t) \epsilon$ 
6:      $z \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $z = \mathbf{0}$ 
7:      $x_{t-1}^{\text{unknown}} = \frac{1}{\sqrt{\alpha_t}} \left( x_t - \frac{\beta_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_\theta(x_t, t) \right) + \sigma_t z$ 
8:      $x_{t-1} = m \odot x_{t-1}^{\text{known}} + (1 - m) \odot x_{t-1}^{\text{unknown}}$ 
9:     if  $u < U$  and  $t > 1$  then
10:       $x_t \sim \mathcal{N}(\sqrt{1 - \beta_{t-1}} x_{t-1}, \beta_{t-1} \mathbf{I})$ 
11:    end if
12:  end for
13: end for
14: return  $x_0$ 
```

# Noise Estimation for Generative Diffusion Models\*

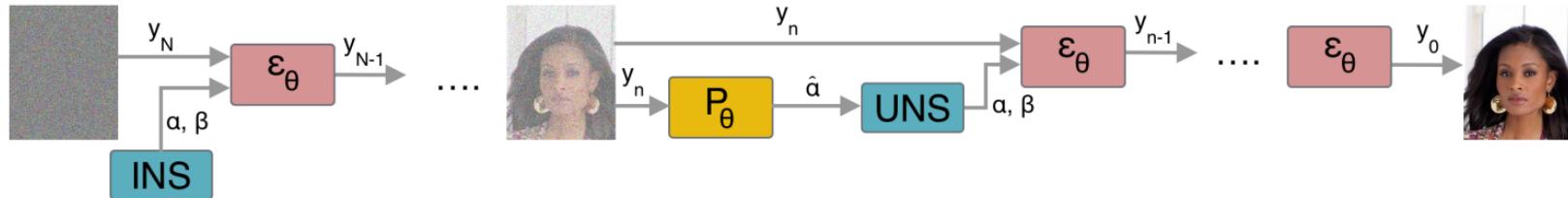


Figure 1: An overview of our generative process. INS and UNS are respectively the functions initializeNoiseSchedule() and updateNoiseSchedule( $\hat{\alpha}$ ).

---

### Algorithm 3: $P_\theta$ training procedure

---

```

1: repeat
2:    $y_0 \sim q(y_0)$ 
3:    $s \sim \mathcal{U}(\{1, \dots, N\})$ 
4:    $\sqrt{\bar{\alpha}} \sim \mathcal{U}([l_{s-1}, l_s])$ 
5:    $\varepsilon \sim \mathcal{N}(0, I)$ 
6:    $y_s = \sqrt{\bar{\alpha}}y_0 + \sqrt{1 - |\bar{\alpha}|}\varepsilon$ 
7:    $\hat{\alpha} = P_\theta(y_s)$ 
8:   Take gradient descent step on:  

     $\| \log(1 - \bar{\alpha}) - \log(1 - \hat{\alpha}) \|_2$ 
9: until converged

```

---



---

### Algorithm 4: Model inference procedure

---

```

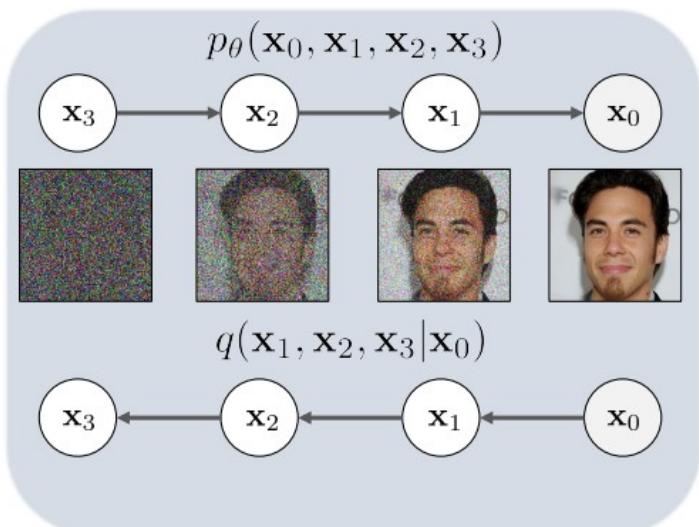
1:  $N$  Number of iterations
2:  $y_N \sim \mathcal{N}(0, I)$ 
3:  $\alpha, \beta = \text{initialNoiseSchedule}()$ 
4: for  $n = N, \dots, 1$  do
5:    $z \sim \mathcal{N}(0, I)$ 
6:    $\hat{\varepsilon} = \varepsilon_\theta(y_n, \sqrt{\bar{\alpha}_n})$  or  $\varepsilon_\theta(y_n, t)$  where  $\bar{\alpha}_n \in [l_t, l_{t-1}]$ 
7:    $y_{n-1} = \frac{y_n - \frac{1 - \alpha_n}{\sqrt{1 - \bar{\alpha}_n}}\hat{\varepsilon}}{\sqrt{\alpha_n}}$ 
8:   if  $n \in U$  then
9:      $\hat{\alpha} = P_\theta(y_{n-1})$ 
10:     $\alpha, \beta, \tau = \text{updateNoiseSchedule}(\hat{\alpha}, n)$ 
11:   end if
12:   if  $n \neq 1$  then
13:      $y_{n-1} = y_{n-1} + \sigma_n z$ 
14:   end if
15: end for
16: return  $y_0$ 

```

---

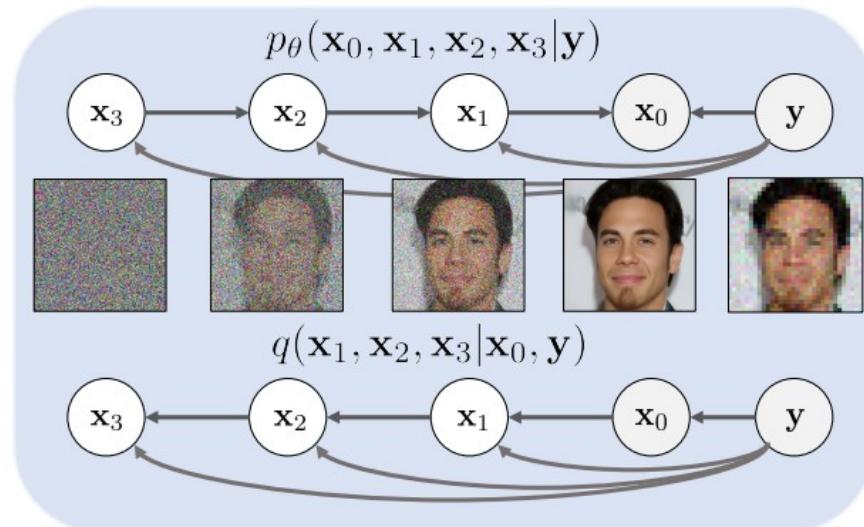
# Denoising Diffusion Restoration Models (DDRM)\*

An efficient, unsupervised posterior sampling method



Denoising Diffusion Probabilistic Models  
(Independent of inverse problem)

Use pre-trained  
models for linear  
inverse problems



Denoising Diffusion Restoration Models  
(Dependent on inverse problem)

# Dual Diffusion Implicit Bridges for Image-to-Image Translation\*

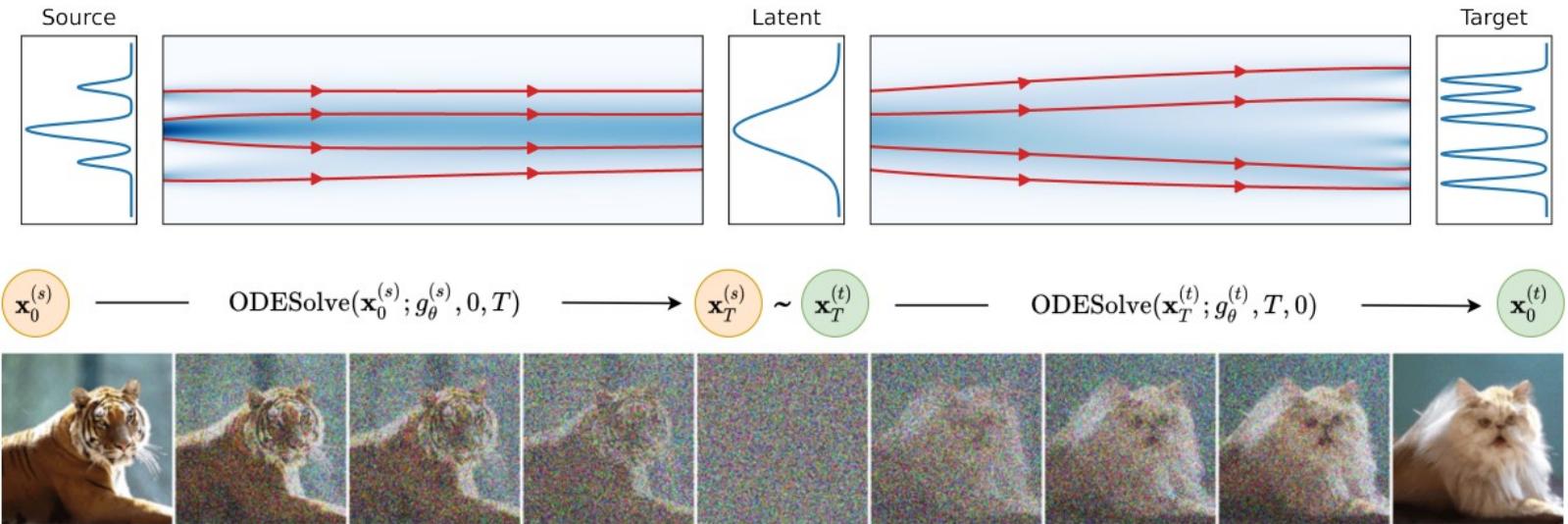
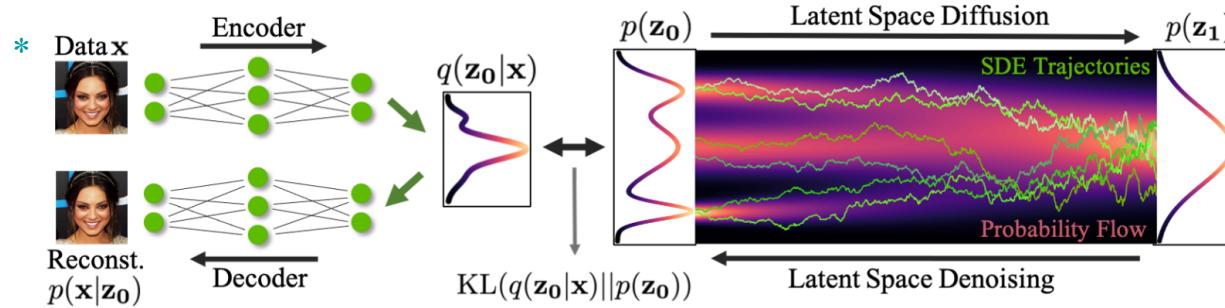
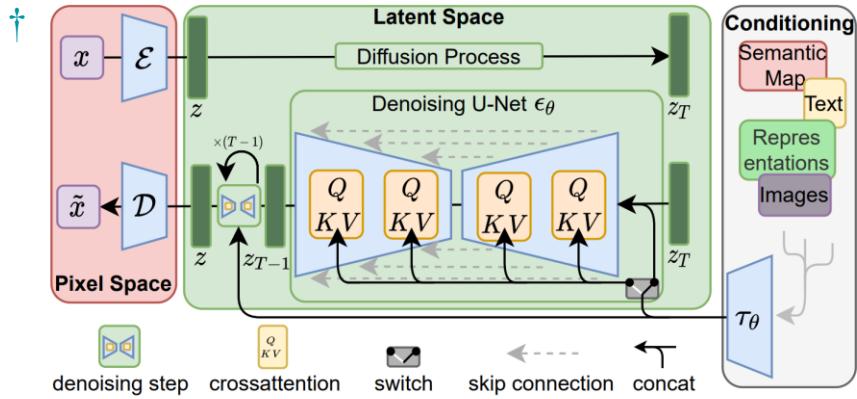


Figure 1: **Dual Diffusion Implicit Bridges:** DDIBs leverage two ODEs for image translation. Given a source image  $\mathbf{x}_0^{(s)}$ , the source ODE runs in the forward direction to convert it to the latent  $\mathbf{x}_T^{(s)}$ , while the target, reverse ODE then constructs the target image  $\mathbf{x}_0^{(t)}$ . (Top) Illustration of the DDIB idea between two one-dimensional distributions. (Bottom) DDIB from a tiger to a cat using a pre-trained conditional diffusion model.

# Score-based Generative Modeling in Latent Space\*

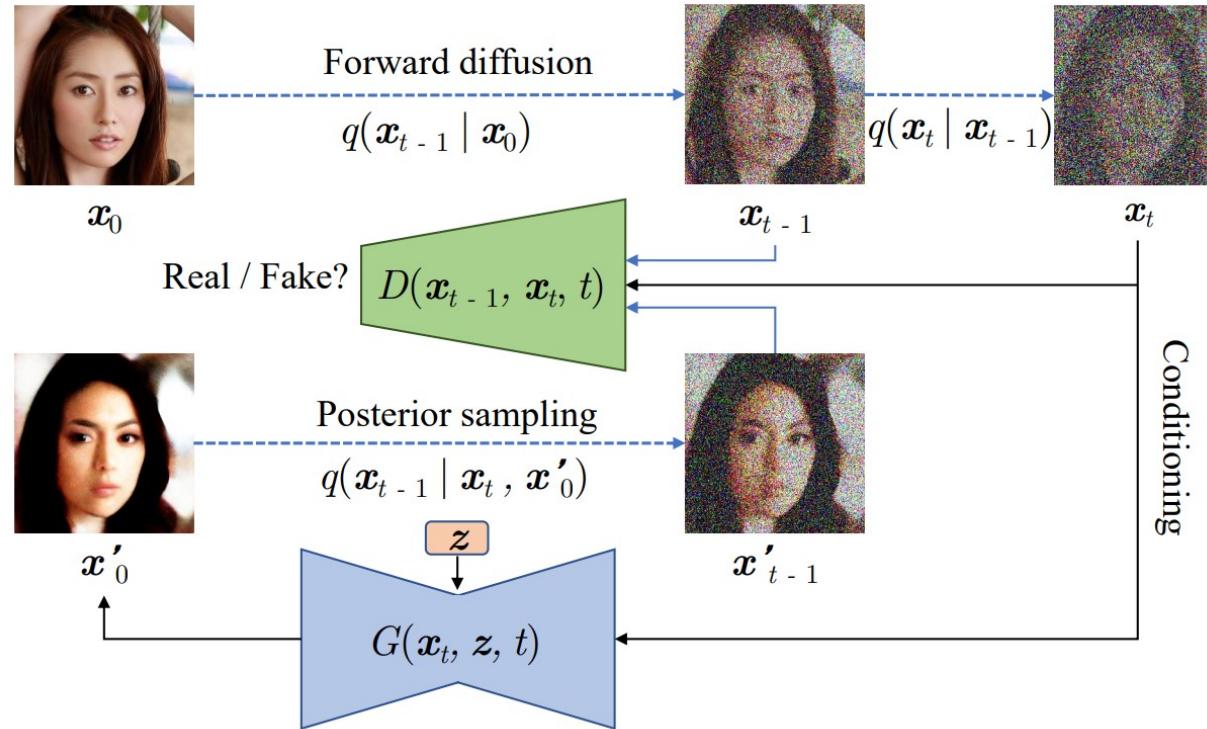
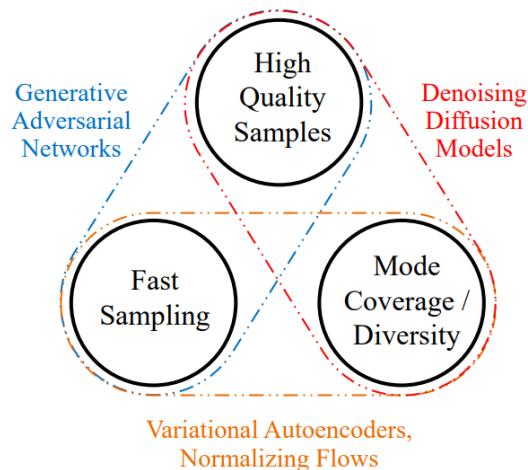
Faster diffusion  
in latent space



†[2112.10752] High-Resolution Image Synthesis with Latent Diffusion Models (arxiv.org)

\*[2106.05931] Score-based Generative Modeling in Latent Space (arxiv.org)

# Tackling the Generative Learning Trilemma with Denoising Diffusion GANS\*



Thank You!

# Useful Resources

- [What's the score? – Review of latest Score Based Generative Modeling papers](#)
- [zhangbaijin/Diffusion-model-low-level \(github.com\)](#)
- [What are Diffusion Models? | Lil'Log \(lilianweng.github.io\)](#)
- [Generative Modeling by Estimating Gradients of the Data Distribution | Yang Song](#)
- [Diffusion Models as a kind of VAE](#)
- [yang-song/score\\_sde\\_pytorch](#)
- [Denoising Diffusion Probabilistic Models \(DDPM\) \(labml.ai\)](#)
- [Denoising Diffusion-based Generative Modeling: Foundations and Applications](#)